



Oregon State University
College of Forestry

Background information regarding RAC questions 5 and 7

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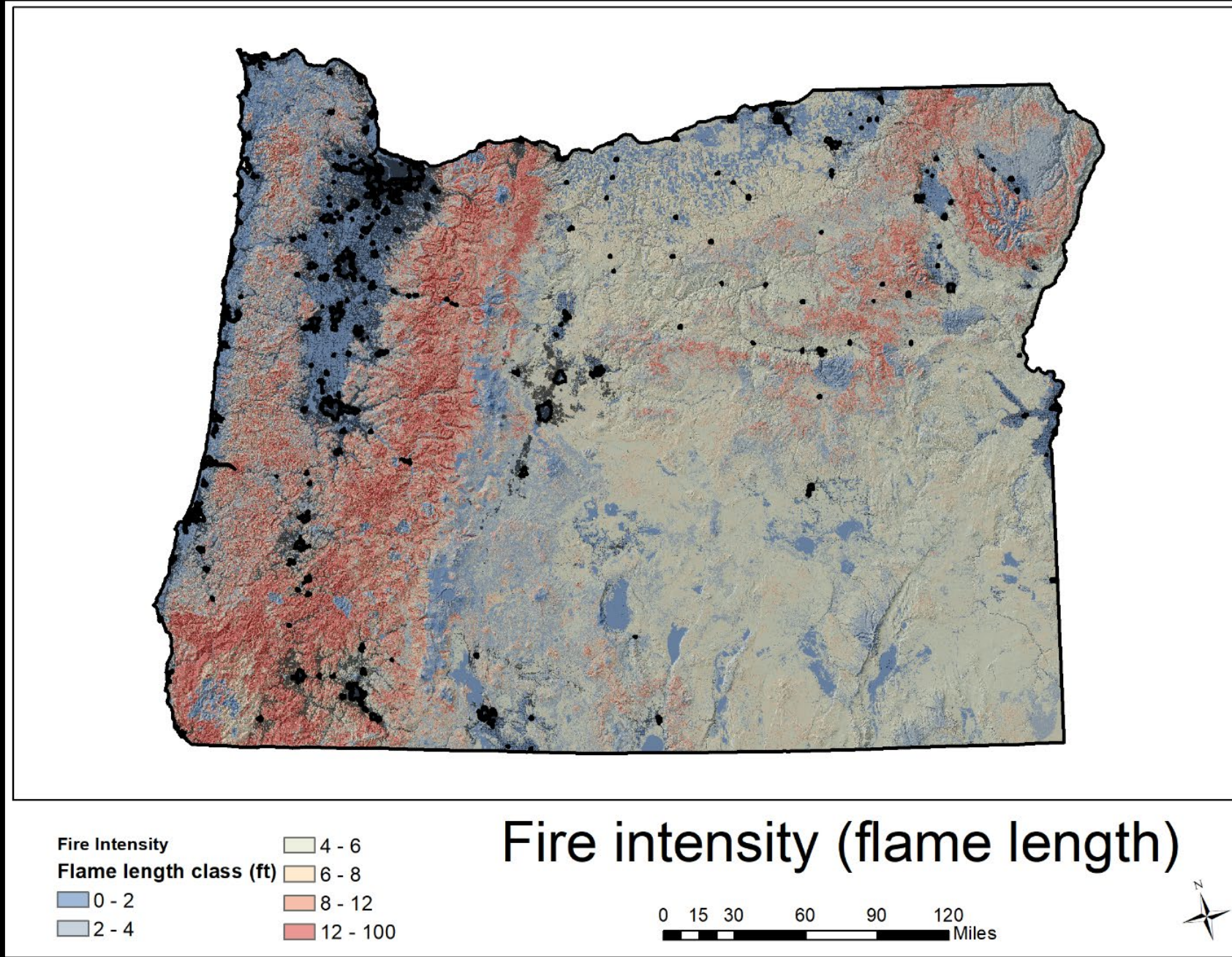


Conditional flame length estimated
in the 2017 PNW Quantitative
Wildfire Risk Assessment

Black areas are the locations of
Where People Live, the dataset used
in the 2017 PNW QRA to capture
consequences to communities.

These estimates are being updated
as per SB 762 requirements so they
will change

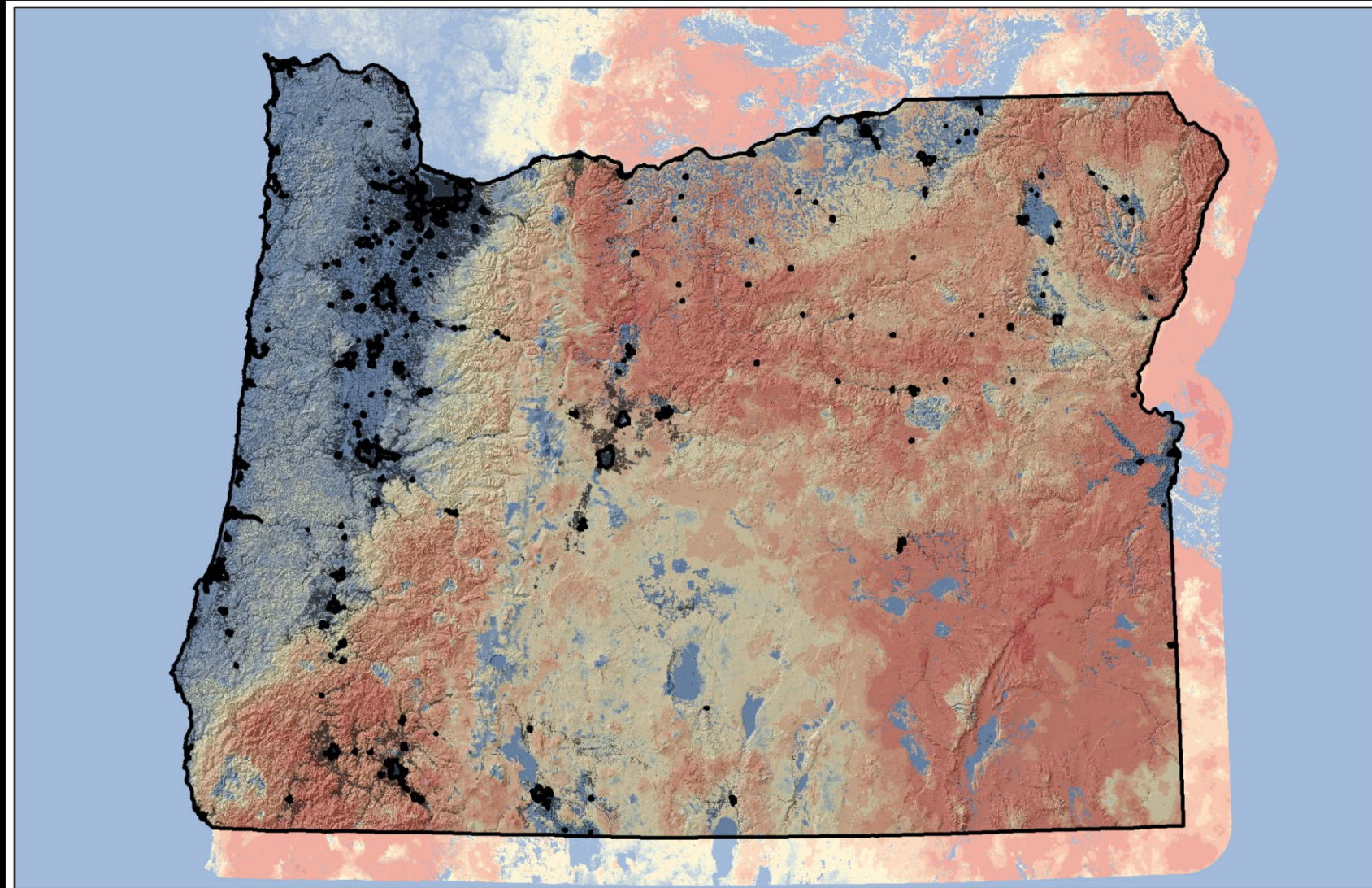
Note: Conditional means that these
flame lengths are conditional on fire
occurrence



Burn probability estimated in the 2017 PNW Quantitative Wildfire Risk Assessment

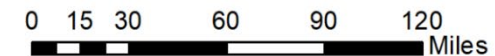
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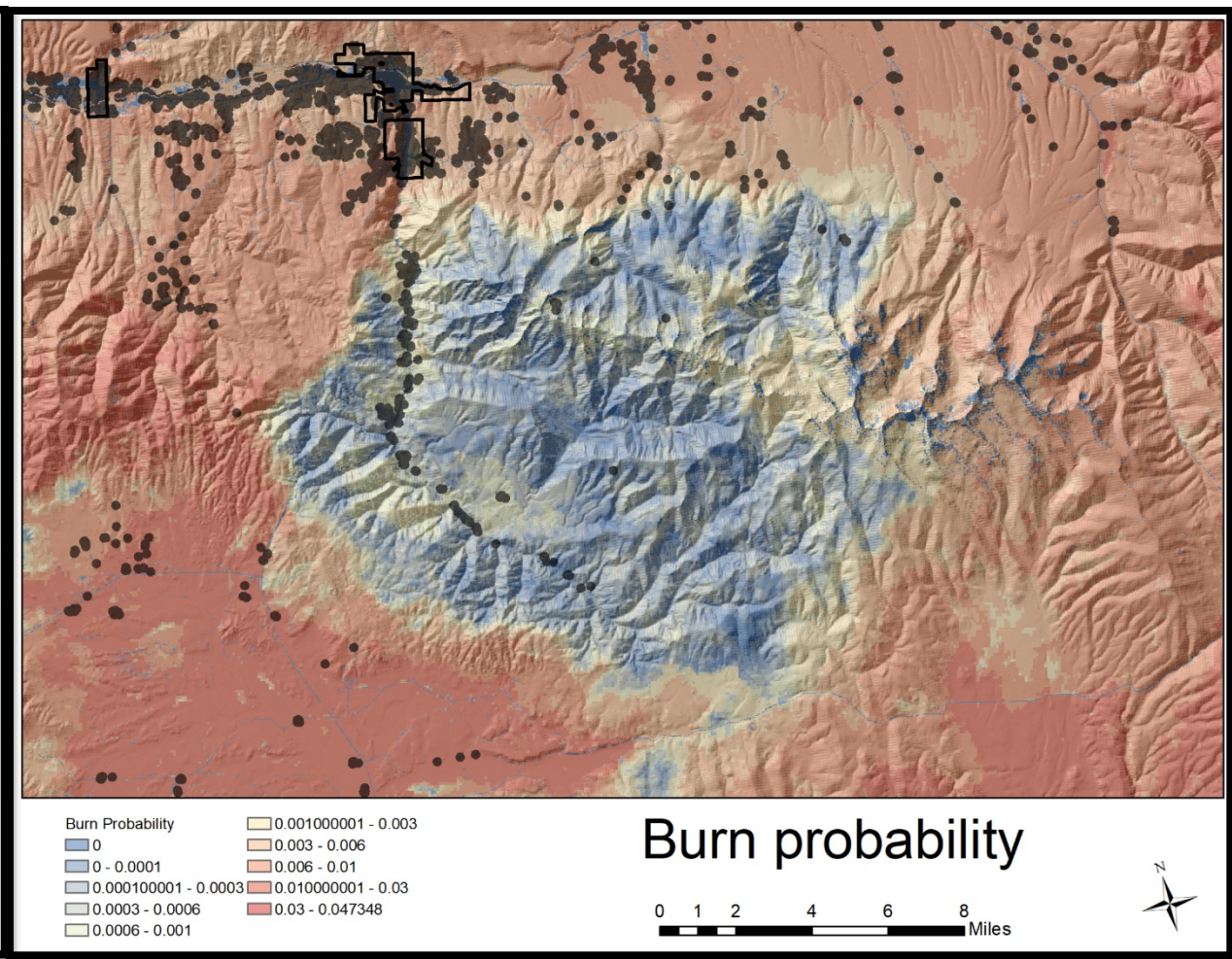
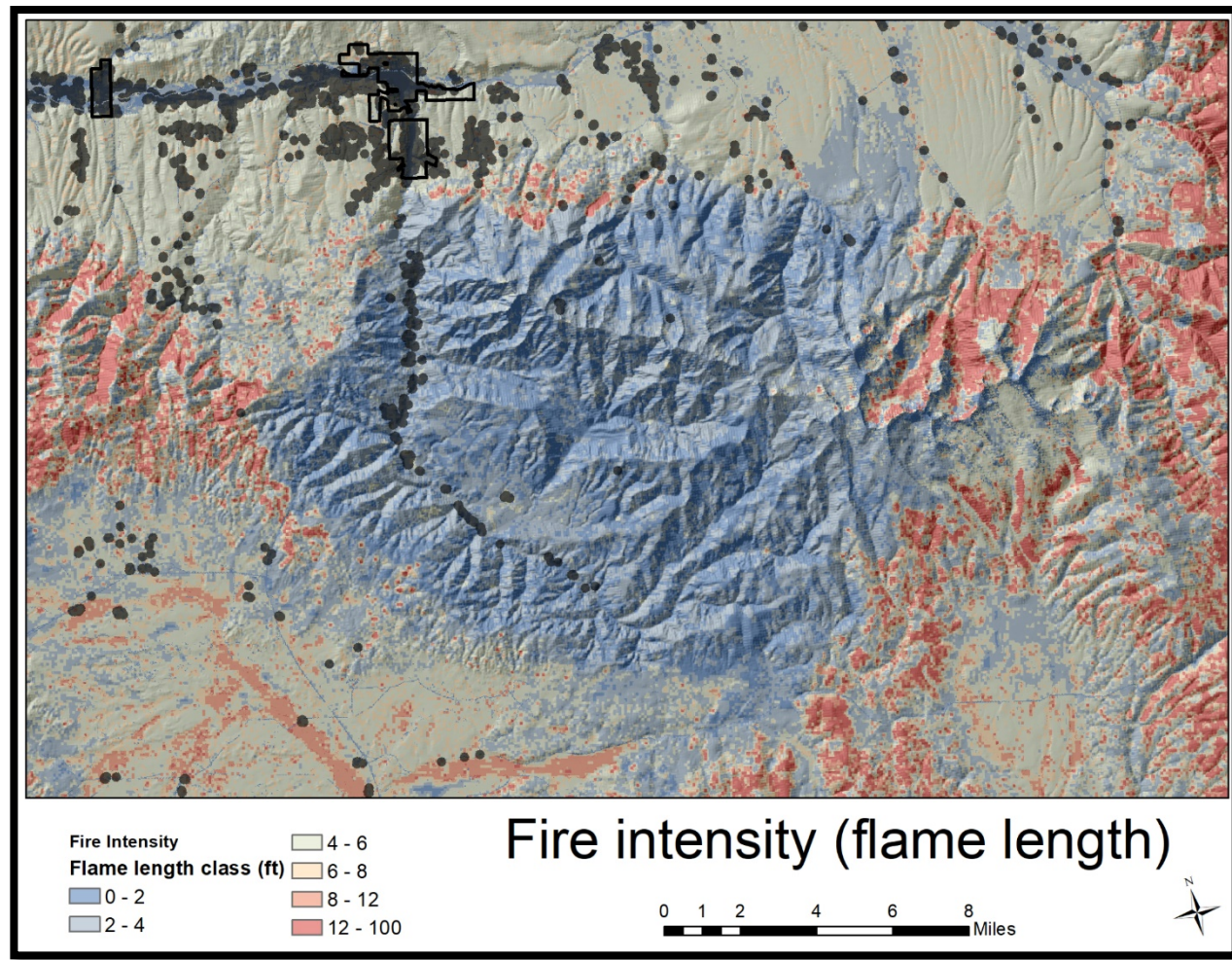
These estimates are being updated as per SB 762 requirements so they will change



Burn Probability	
0	0.001000001 - 0.003
0 - 0.0001	0.003 - 0.006
0.000100001 - 0.0003	0.006 - 0.01
0.0003 - 0.0006	0.010000001 - 0.03
0.0006 - 0.001	0.03 - 0.047348

Burn probability





SB 762 Section 7(4):

In consultation with Oregon State University, the department shall establish five statewide wildfire risk classes of extreme, high, moderate, low and no risk.

The following examples came from a “toy dataset”, which used existing datasets but not the official datasets that will come out of this process since we are still deciding upon the WUI definition and producing the fire hazard data layers. However, it’s a reasonable approximation of the outcomes and a strong basis for the risk classification discussion.

We selected housing unit densities greater than or equal to 1 (presence or absence) and evaluated their exposure to wildfire based on burn probability and fire intensity, as described in subsequent slides.



Integrating HVRA with differing units of measure (for example, habitat vs. homes) requires relative importance (RI) values for each HVRA/sub-HVRA. These values were identified in the RI workshop, as discussed in Section 3. The final importance weight used in the risk calculations is a function of overall HVRA importance, sub-HVRA importance, and relative extent (pixel count) of each sub-HVRA. This value is therefore called relative importance per pixel (RIPP).

The RF and RIPP values were combined with estimates of the flame-length probability (FLP) in each of the six flame-length classes to estimate conditional NVC (cNVC) as the sum-product of flame-length probability (FLP) and response function value (RF) over all the six flame-length classes, with a weighting factor adjustment for the relative importance per unit area of each HVRA, as follows:

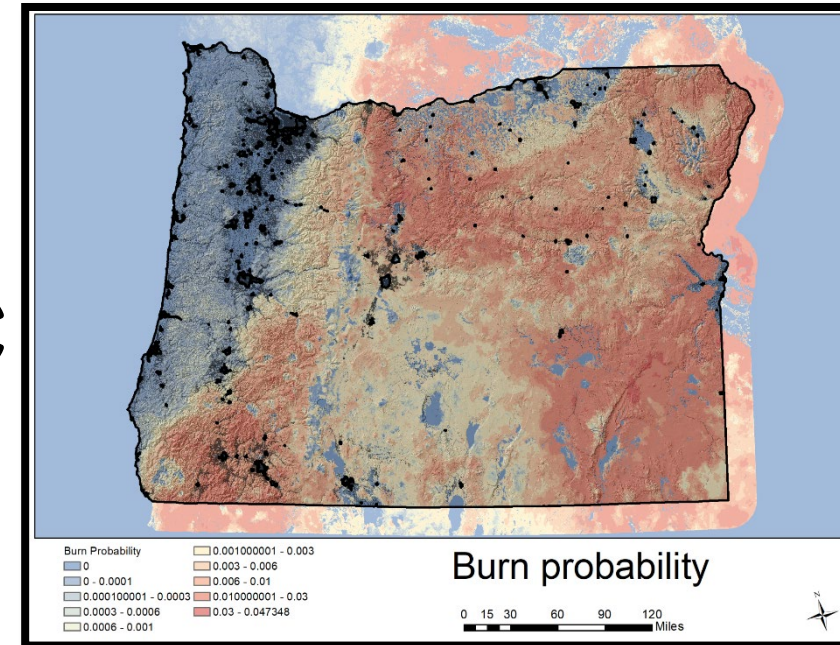
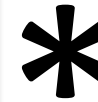
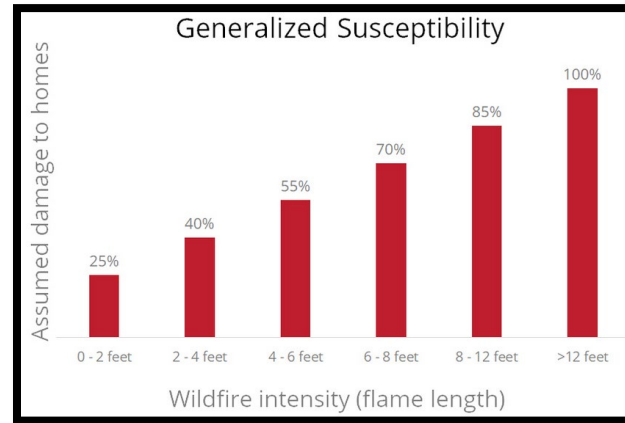
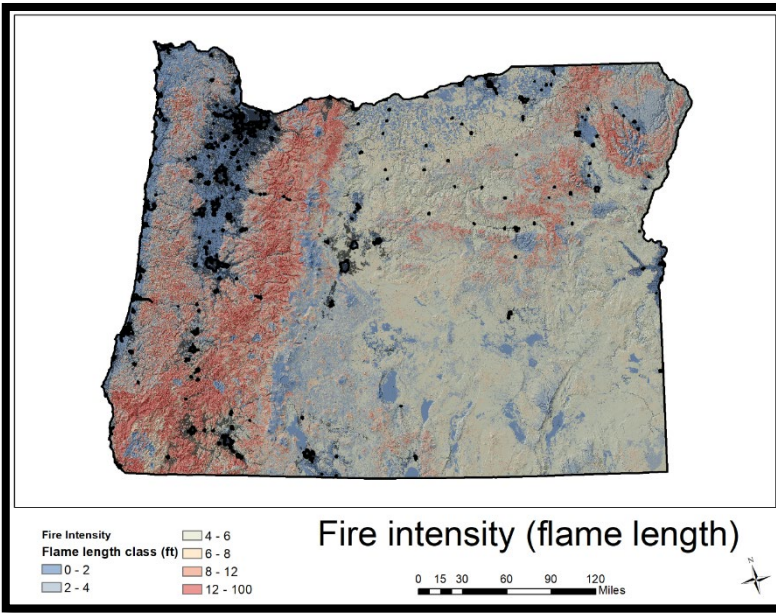
$$cNVC_j = \sum_i^n FLP_i * RF_{ij} * RIPP_j$$

where i refers to flame length class ($n = 6$), j refers to each HVRA, and RIPP is the weighting factor based on the relative importance and relative extent (number of pixels) of each HVRA. The cNVC calculation shown above places each pixel of each resource on a common scale (relative importance), allowing them to be summed across all resources to produce the total cNVC at a given pixel:

$$cNVC = \sum_j^m cNVC_j$$

where cNVC is calculated for each pixel in the analysis area. Finally, eNVC for each pixel is calculated as the product of cNVC and annual BP:

$$eNVC = cNVC * BP$$



Conditional net value change
(consequences given fire occurrence)

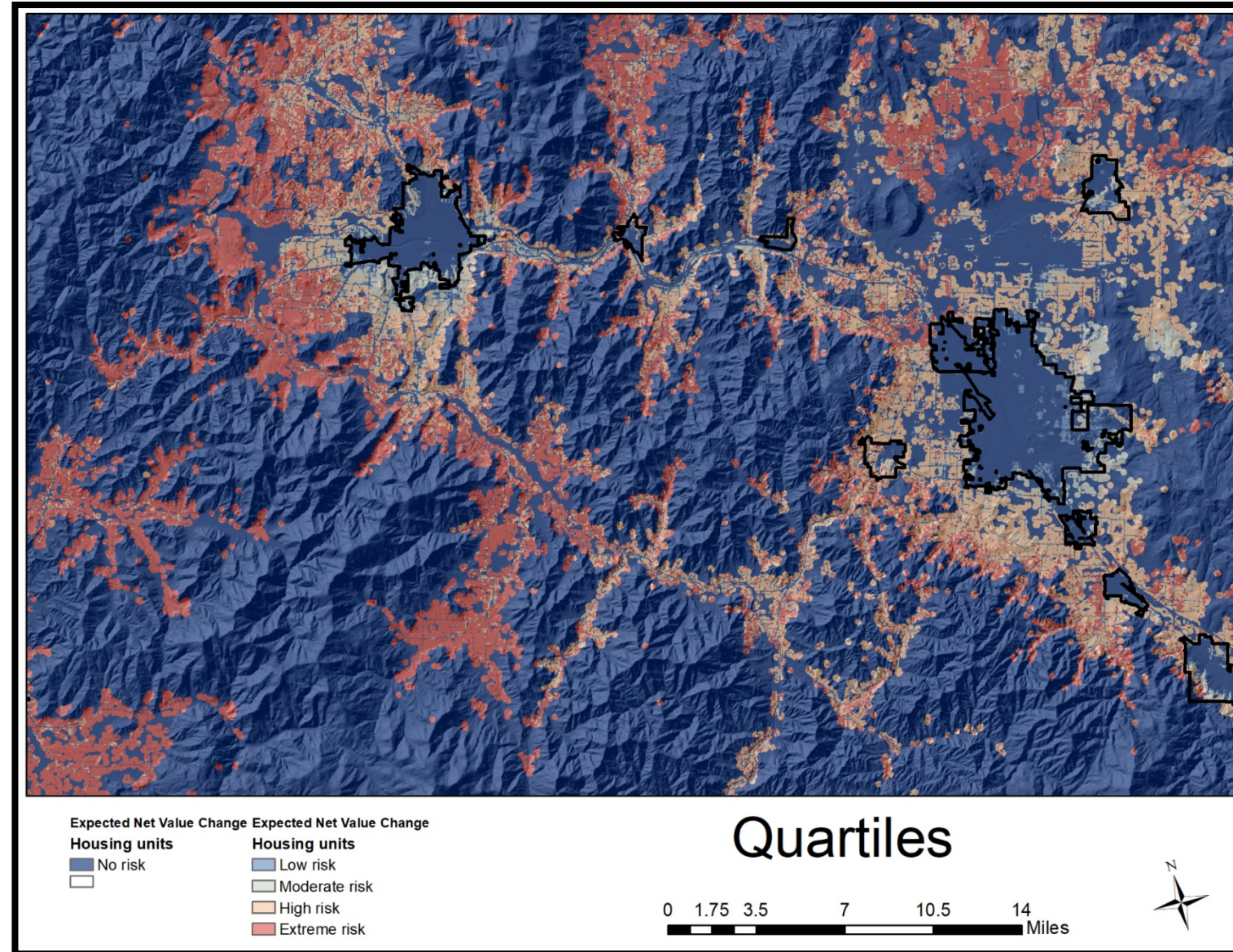
Expected net value change
(estimate of likely consequences)



In quantile classification, each class contains an equal number of features. A quantile classification is well suited to linearly distributed data. Quantile assigns the same number of data values to each class. There are no empty classes or classes with too few or too many values.

Because features are grouped in equal numbers in each class using quantile classification, the resulting map can often be misleading. Similar features can be placed in adjacent classes, or features with widely different values can be put in the same class. You can minimize this distortion by increasing the number of classes.

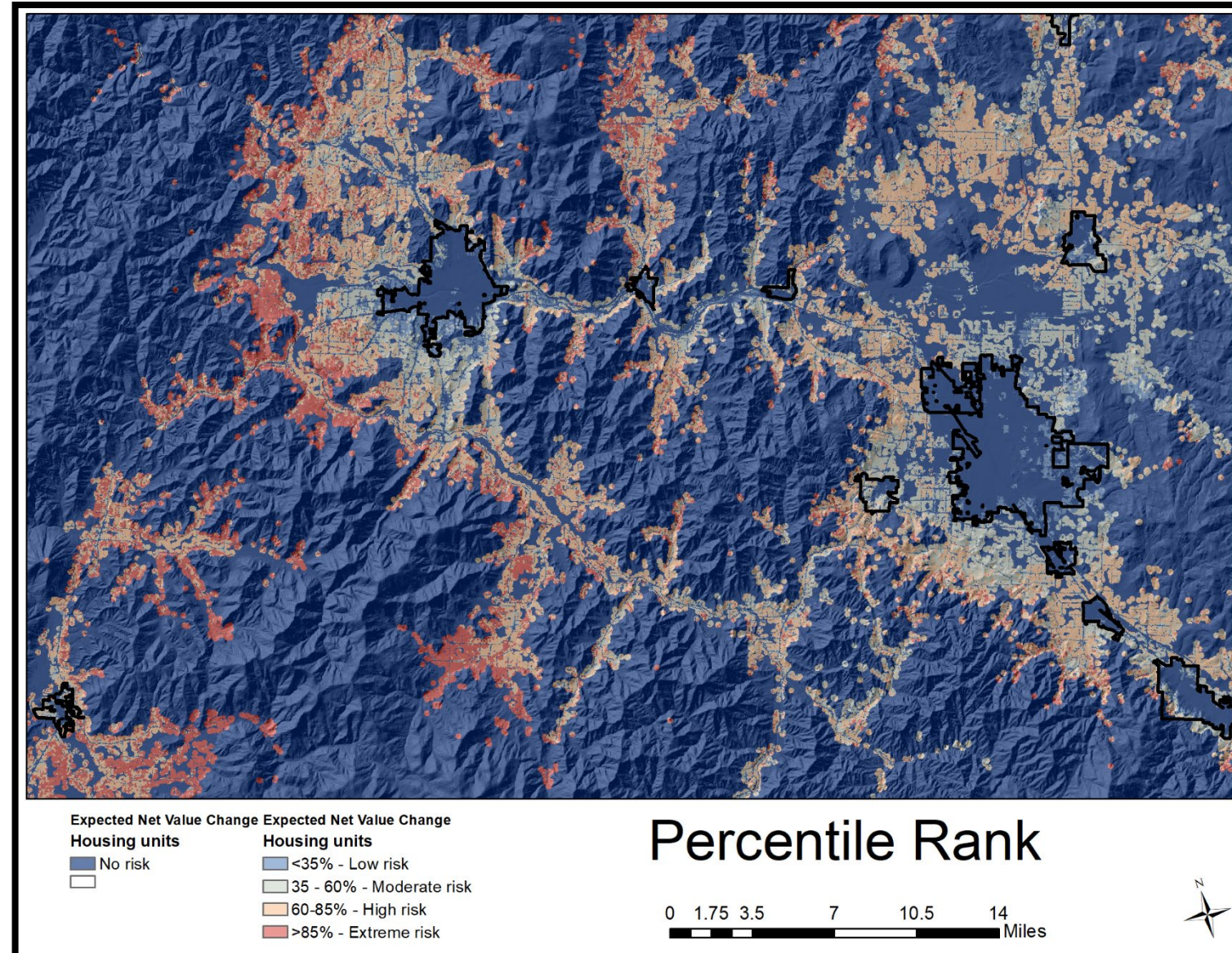
Arc Pro documentation



For percentile ranking, I created 20 classes that included equal number of features (quantile classification) that resulted in 5% groupings of values. In other words, 5% of the data is present in each class, and since these classes are listed in order along the scale of the data, the lowest class limit represents the bottom 5% of the data, the second class limit the bottom 10%, third class limit the bottom 15%, and so on.

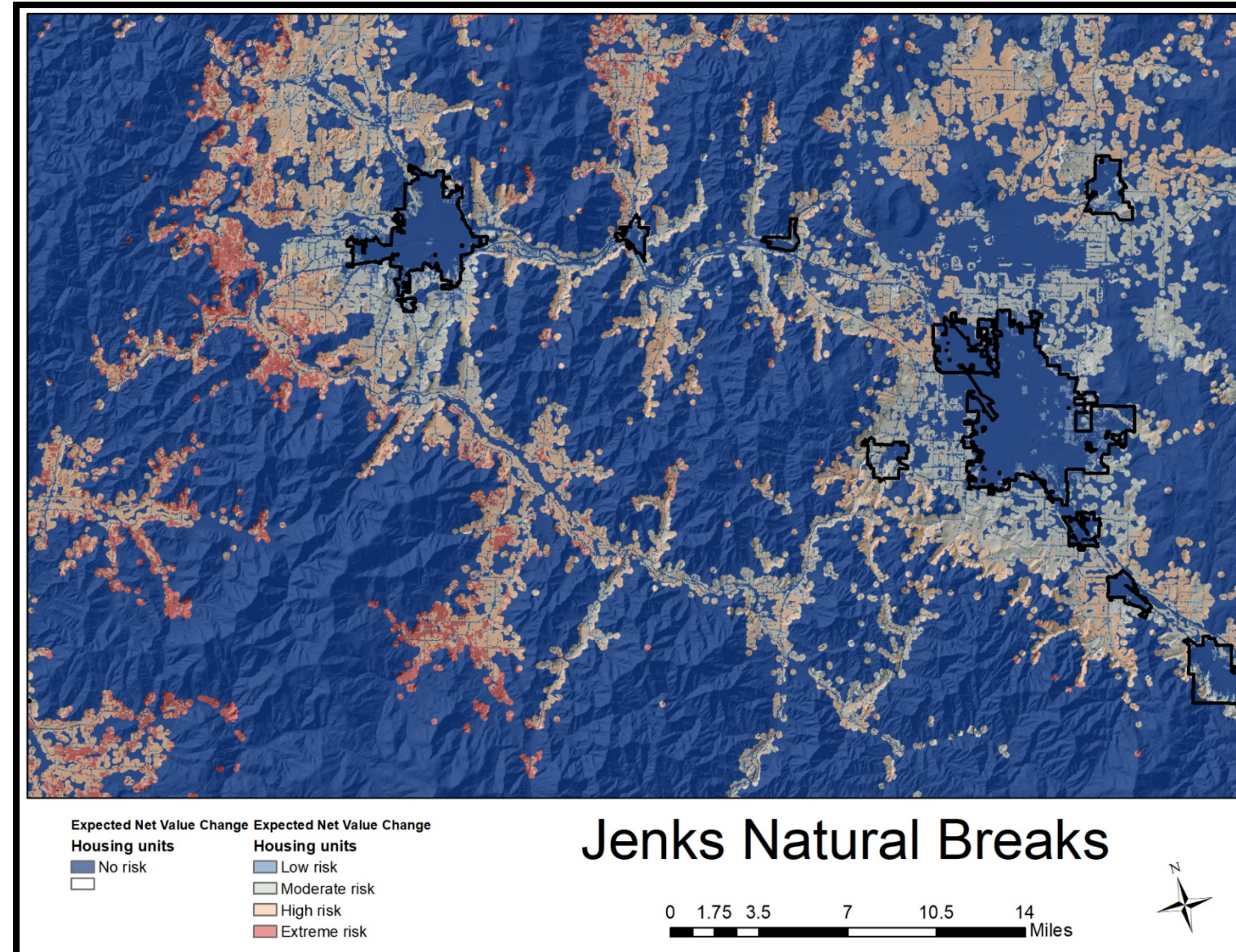
I then selected the threshold value from the class that represented the percentile ranks where;

< 35% is low risk,
 35 – 60% is moderate risk,
 60 - 85% is high risk,
 > 85% is extreme risk.



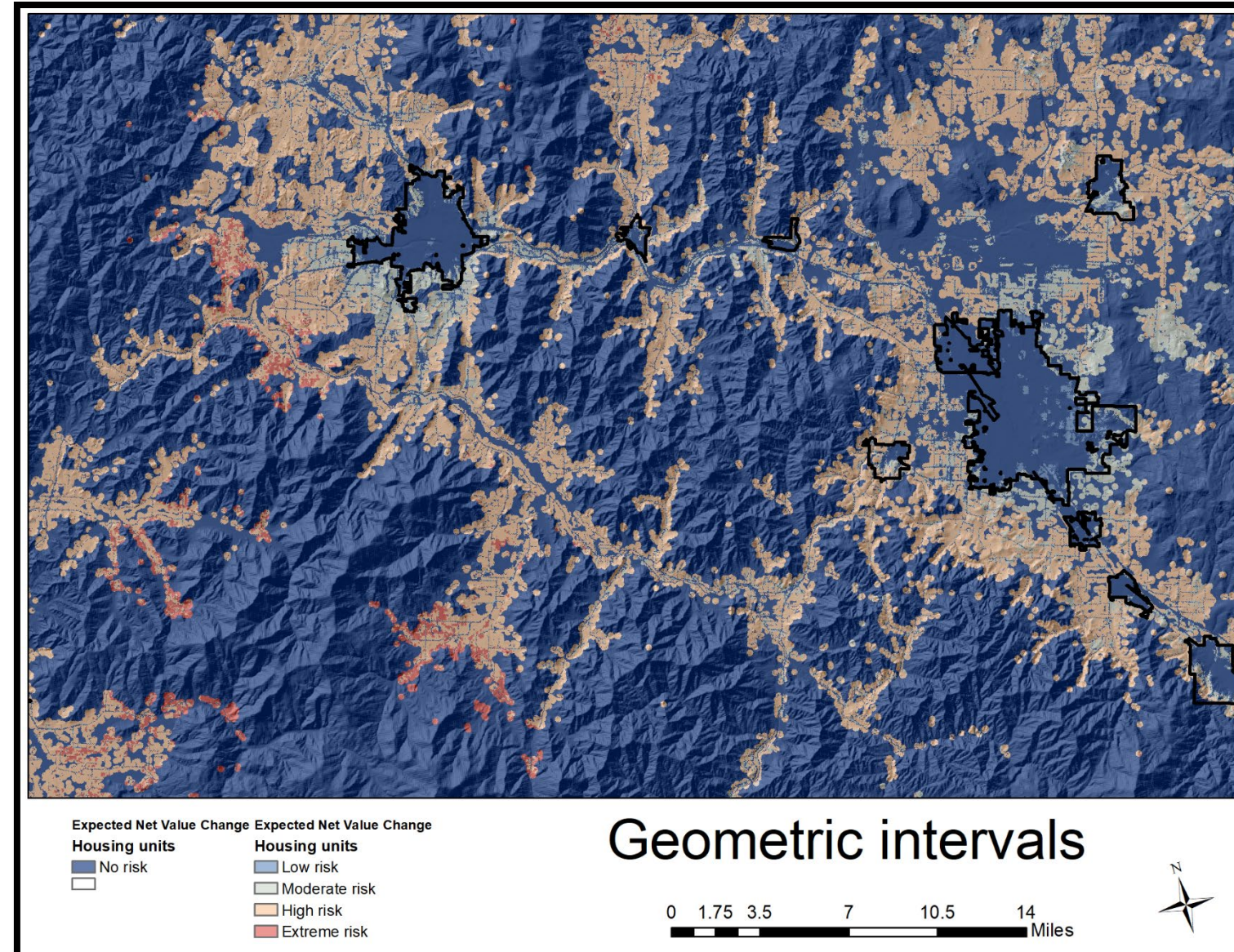
With natural breaks classification (Jenks), classes are based on natural groupings inherent in the data. Class breaks are created in a way that best groups similar values together and maximizes the differences between classes. The features are divided into classes whose boundaries are set where there are relatively big differences in the data values.

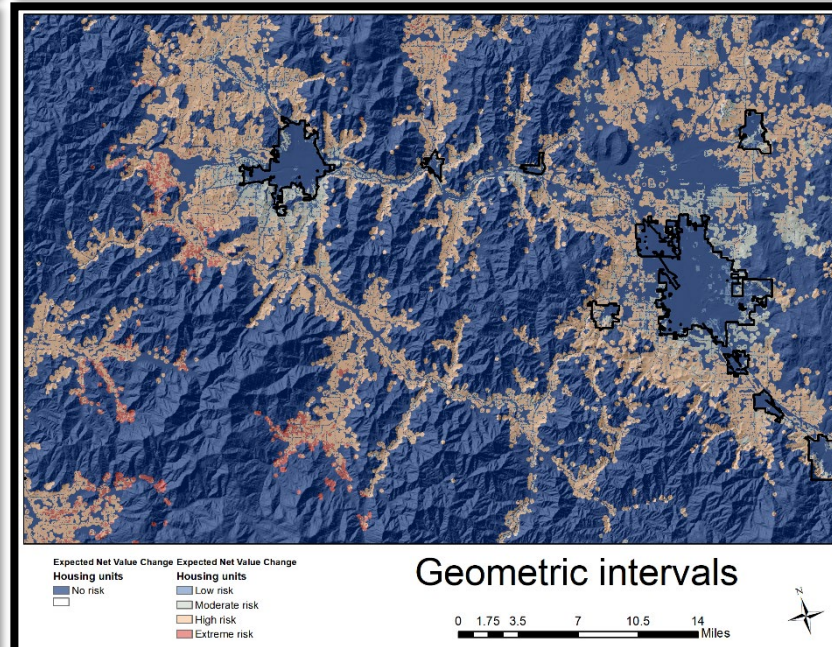
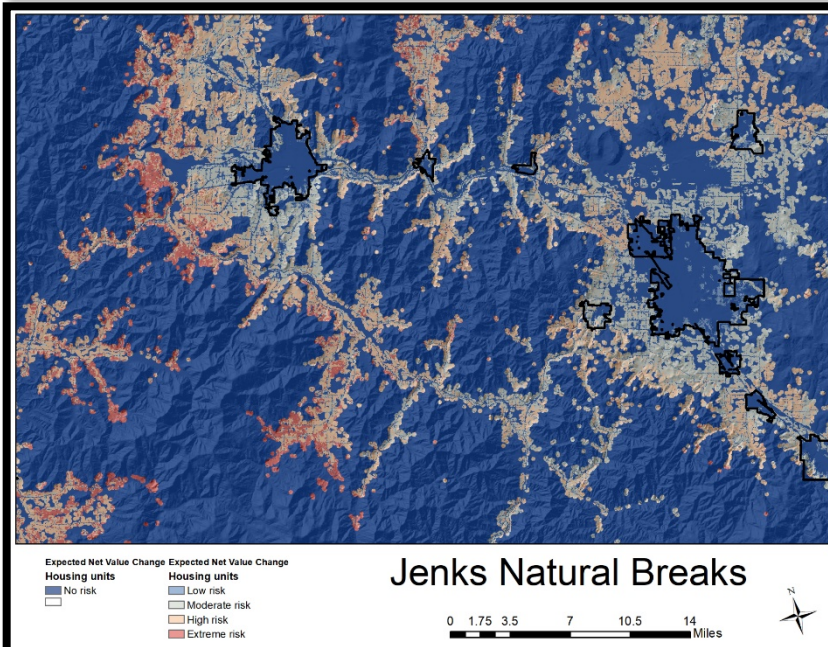
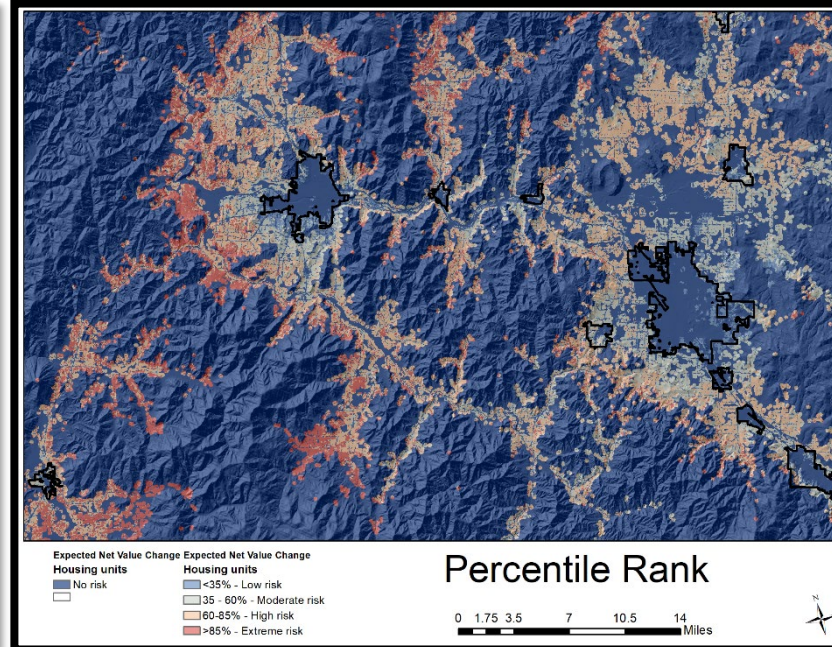
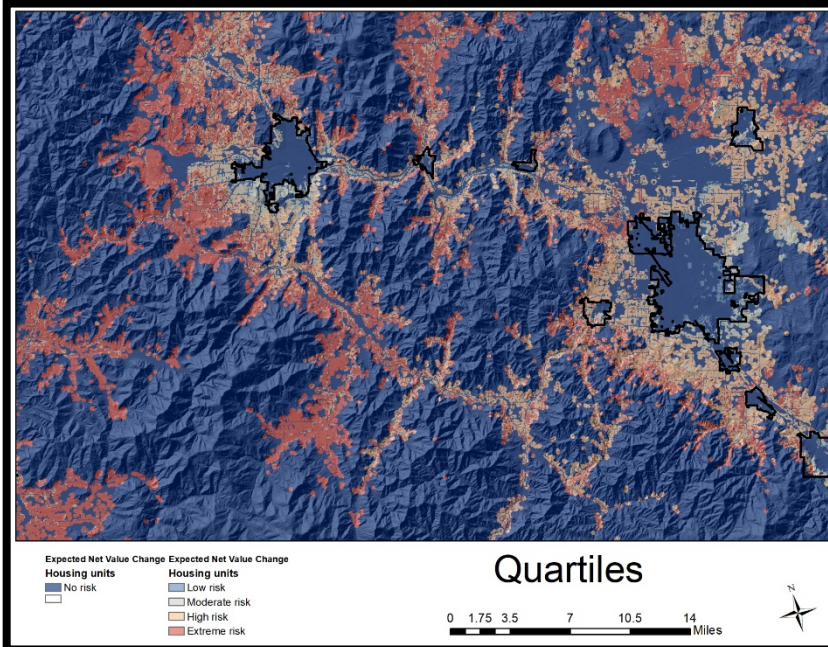
This classification method seeks to minimize the average deviation from the class mean while maximizing the deviation from the means of the other groups. The method reduces the variance within classes and maximizes the variance between classes

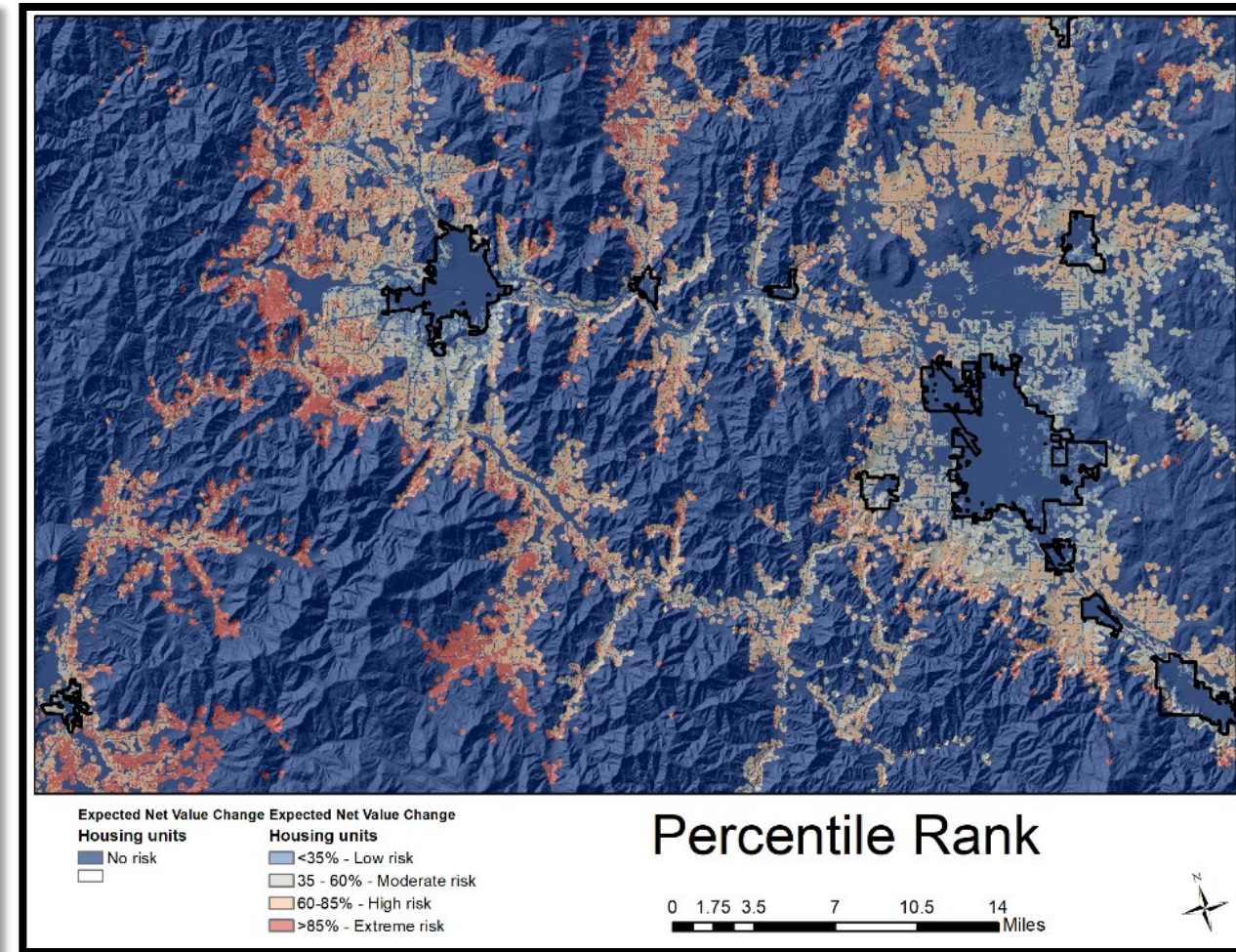
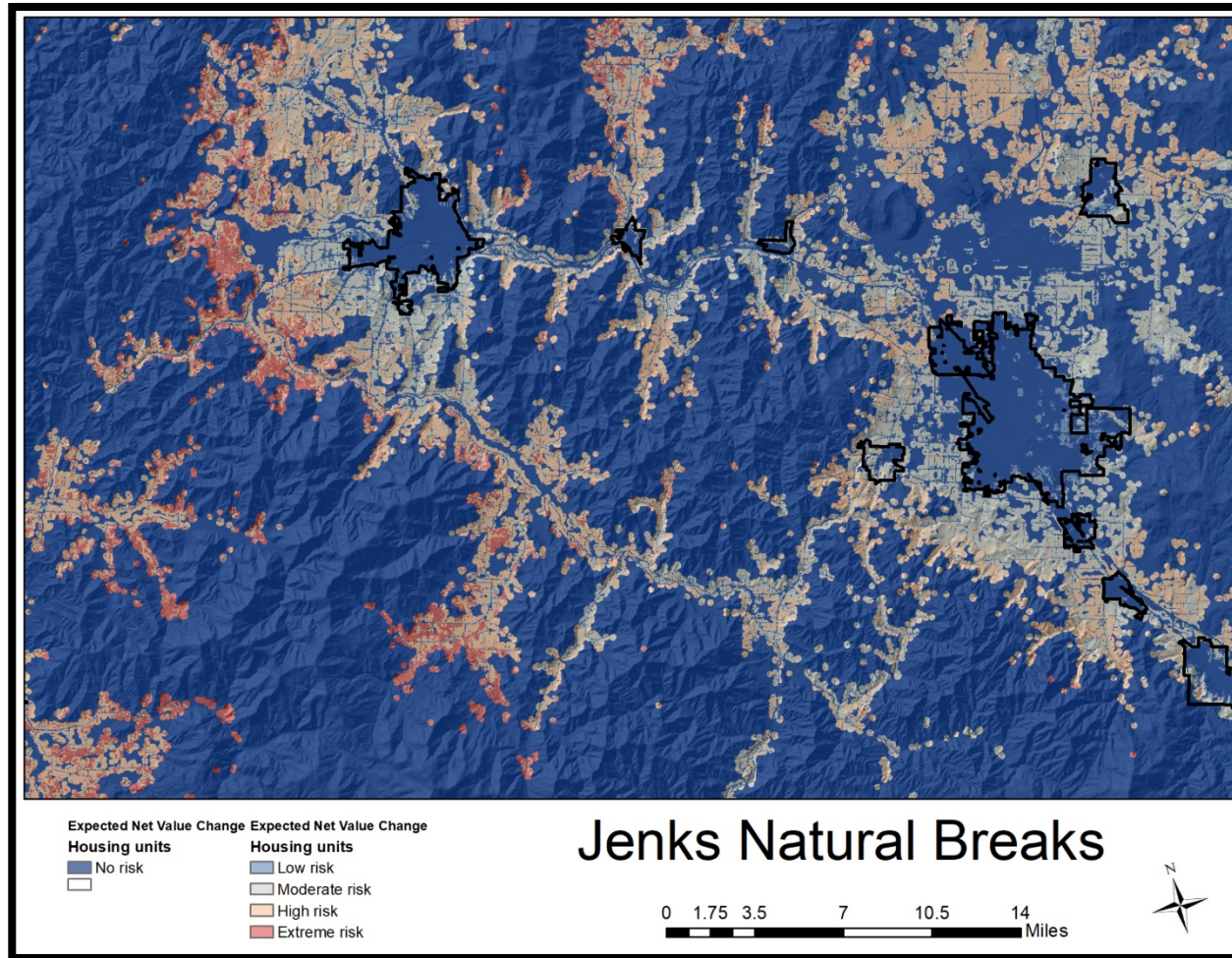


The geometrical interval classification scheme creates class breaks based on class intervals that have a geometric series. The geometric coefficient in this classifier can change once (to its inverse) to optimize the class ranges. The algorithm creates geometric intervals by minimizing the sum of squares of the number of elements in each class. This ensures that each class range has approximately the same number of values in each class and that the change between intervals is fairly consistent.

This algorithm was specifically designed to accommodate continuous data. It is a compromise between the equal interval, natural breaks (Jenks), and quantile methods. It creates a balance between highlighting changes in the middle values and the extreme values, thereby producing a result that is visually appealing and cartographically comprehensive.







Correlation with Percentiles

Low	< 35%
Moderate	35% to 75%
High	75% to 95%
Extreme	> 95%

Percentile Ranks

Low	< 35%
Moderate	35% to 60%
High	60% to 85%
Extreme	> 85%